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Theoretical Paper No. 66

EVALUATING PRIORITY EFFECTS IN FREE RECALL

by

Lawrence J. Hubert and Joel R. Levin

Report from the Project on
Children's Learning and Development

Joel R. Levin
Faculty Associate

Wisconsin Research and Development
Center for Cognitive Learning
The University of Wisconsin
Madison, Wisconsin

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A randomization model appropriate for evaluating priority effects in free recall (i.e., whether "new" items are recalled prior to "old" items) is discussed and related to well-known nonparametric significance tests. Since the bases for the measures that have been suggested in the psychological literature may be interpreted either in terms of Wilcoxon's rank sum statistic or through a specific entry in a 2 x 2 contingency table, alternative indices of priority can be adopted directly from classical nonparametric statistics. Finally, the mean and variance formulas for a general correlational statistic are provided that specialize to the moments for the two measures already in common use.

I

INTRODUCTION

Most of the quantitative literature that has dealt with the free-recall learning paradigm has emphasized the measurement problems encountered in identifying category "clustering" within a subject's protocol (see Shuell, 1969). Although this interest may be due in part to historical precedents, it is still surprising that a related and well-known phenomenon from the same experimental literature, called the "priority effect" (see Postman, 1972), has been virtually ignored by methodologists. The only relevant paper appears to be the recent contribution by Flores and Brown (1974). To be more specific, suppose that a subject is required to learn a list of items over several trials: Priority is evidenced whenever the subject recalls a "new" item on a particular trial (i.e., an item emitted for the first time) prior to recalling an "old" item (i.e., an item already recalled on one or more previous trials). Apparently, no general methodology has been proposed for assessing priority effects comparable to what now exists for evaluating category clustering, even though exactly the same class of randomization procedures is appropriate in both instances.

It is not the intent of this paper to develop any radically new inference models for assessing priority effects; in fact, the discussion merely illustrates how randomization concepts that are very familiar in nonparametric statistics may be applied to this rather specific experi-

mental paradigm of interest to psychologists working in the area of memory organization. Once the general statistical framework has been developed, the two measures of the priority phenomenon that have been suggested by other authors can be related directly to common nonparametric significance tests. More importantly, this relationship suggests possible extensions of the basic concept of priority to include alternative experimental hypotheses that involve more than a simple zero-one (i.e., "old" - "new") categorization of the items. For instance, concepts that are measurable on a more comprehensive scale, such as meaningfulness, frequency, concreteness, and the like, can be evaluated in essentially the same manner, as long as the appropriate statistical generalizations are developed at the outset.

Finally, the nonparametric connections provide several formal indices of priority--especially for the usual dichotomous application--that have the same type of operational interpretation as advocated by Goodman and Kruskal (1954) in their classic paper on measuring association in a contingency table. Since the Goodman-Kruskal arguments for a "good" measure of association are rather well-accepted in psychology (see Hays, 1973, Chapters 17 and 18), it is of interest to point out the availability of indices of priority that have similar operational significance.

II

BACKGROUND

As a way of formalizing the problem of measuring priority effects, suppose that on a particular trial a subject recalls n items, $o_1, o_2, \ldots, o_n$, in the order indicated. In other words, o_1 is recalled first, o_2 is recalled second, and so on. Furthermore, each of the objects, o_i, has an associated numerical value, x_i, that denotes some characteristic of the item. In the most common application:

$$(1) \qquad x_i = \begin{cases} 0 & \text{if } o_i \text{ was recalled on a previous trial (an "old" item);} \\ 1 & \text{if } o_i \text{ was \underline{not} recalled on a previous trial (a "new" item).} \end{cases}$$

Finally, a second variable y_i is attached to o_i that indicates the relative position of the object in the recall sequence; for instance, as one important case to be considered explicitly, we use y_i to denote rank:

$$(2) \qquad y_i = i.$$

For convenience, y_i defined as in (2) will be called a <u>rank function</u>. In summary, when the variable x_i is paired with the corresponding variable y_i, evidence for a priority effect exists if the x_i's that are 1's tend to be paired with the y_i's that are small. (Conversely,

"negative" priority exists if the x_i's that are 1's tend to be paired with the y_i's that are large.)

Since a sequence of n bivariate observations is available using the x_i's and the y_i's, it is natural to consider some type of correlational index for a measure of relationship. As one simple possibility, a raw (or unnormalized) index of the priority effect is obtained by the product-moment statistic

$$\Gamma = \sum_{i=1}^{n} x_i y_i .$$

Given the specifications of x_i and y_i in (1) and (2), respectively, Γ is the sum of the recall ranks for all of the new items, and after a suitable normalization, forms the basis of a measure introduced by Battig, Allen and Jensen (1965). Numerous alternatives for a final normalization exist, however, and consequently, for convenience in the initial discussion, only the index Γ will be considered directly. The problem of obtaining an appropriate normalization will be dealt with in a later section.

Using the general form of the statistic Γ, other possible measures of priority can be developed merely by varying the definition of y_i. As a second important illustration, suppose y_i no longer denotes rank position in recall. Instead, the protocol is first dichotomized at some point, say at the R^{th} recall position, and y_i is given by:

(3)
$$y_i = \begin{cases} 0 & \text{if } i > R; \\ 1 & \text{if } i \leq R. \end{cases}$$

For convenience, y_i defined as in (3) is called a dichotomy function. If the simple definition in (1) for x_i is still appropriate, but y_i is now a dichotomy function, Γ is the number of new items in the first R positions of the protocol. Furthermore, Γ corresponds to an unnormalized version of a measure originally suggested by Postman and Keppel (1968) and Shuell and Keppel (1968).[1]

In short, measures that are based on different scoring functions for y_i lead to different statistics that may have value in assessing priority effects. As a further generalization that was mentioned earlier, the variable x_i itself can be extended beyond the simple zero-one function considered in (1), and Γ still can be used as a measure of a monotonic relationship between recall position and the information regarding the recalled items provided by x_i. Since Γ is the crucial quantity no matter what specific definitions are ultimately selected, the next section discusses a randomization distribution for Γ in some detail. Also, the applications of this randomization distribution for the two special cases discussed in the literature, defined by (1) for x_i and either (2) or (3) for y_i, will be pointed out explicitly.

Although no statistical inference model has been discussed as yet, at least one argument is already apparent for preferring the rank function definition for y_i over the dichotomy function. The dichotomy function uses less information from the protocol, and even on a priori

[1]The index Γ has been keyed in such a way that small values indicate a priority effect for the rank function but large values indicate a priority effect for the dichotomy function. Although this discrepancy is somewhat of an inconvenience, it parallels the available literature.

grounds, would have to be considered less sensitive. Moreover, the loss of protocol information that is "built into" the dichotomy function is not justified by any later statistical advantage, either conceptually or computationally. In fact, the rank function itself is somewhat easier to develop, and in several instances will actually result in simpler formulas.

III

RANDOMIZATION PROCEDURES FOR Γ

Although the value of the index Γ can be calculated with ease, an inference problem still exists in deciding whether the size of Γ is sufficiently extreme to reject a "null" hypothesis of no priority effect. One convenient technique for modeling this "null" hypothesis is through the concept of a permutation distribution well known in nonparametric statistics. In particular, it is assumed that all n! possible ways of assigning the x_i's to the fixed sequence of the y_i's are equally likely a priori. Furthermore, for all n! possible allocations of the x_i's, the values of Γ are obtained and then tabled to form a frequency distribution for Γ, which is then treated as its "null" probability distribution.

As a simple example that may help to clarify the inference process, suppose that n = 4, with 2 new items emitted by the subject in the first and second positions of his protocol. Using the definitions for x_i and y_i in (1) and (2), respectively, we have $x_1 = 1$, $x_2 = 1$, $x_3 = 0$, $x_4 = 0$; and $y_1 = 1$, $y_2 = 2$, $y_3 = 3$, $y_4 = 4$. Assuming that the y_i's are fixed, the 4! = 24 possible orderings of the x_i's and the associated values of Γ are as follows (for later purposes, the last column also presents the index Γ based on the definition for y_i given in (3) for R = 1):

Permutation	Γ (Rank Function)	Γ (Dichotomy Function)
$x_1\ x_2\ x_3\ x_4$	3	1
$x_1\ x_2\ x_4\ x_3$	3	1
$x_1\ x_3\ x_2\ x_4$	4	1
$x_1\ x_3\ x_4\ x_2$	5	1
$x_1\ x_4\ x_2\ x_3$	4	1
$x_1\ x_4\ x_3\ x_2$	5	1
$x_2\ x_1\ x_3\ x_4$	3	1
$x_2\ x_1\ x_4\ x_3$	3	1
$x_2\ x_3\ x_1\ x_4$	4	1
$x_2\ x_3\ x_4\ x_1$	5	1
$x_2\ x_4\ x_1\ x_3$	4	1
$x_2\ x_4\ x_3\ x_1$	5	1
$x_3\ x_1\ x_2\ x_4$	5	0
$x_3\ x_1\ x_4\ x_2$	6	0
$x_3\ x_2\ x_1\ x_4$	5	0
$x_3\ x_2\ x_4\ x_1$	6	0
$x_3\ x_4\ x_1\ x_2$	7	0
$x_3\ x_4\ x_2\ x_1$	7	0
$x_4\ x_1\ x_2\ x_3$	5	0
$x_4\ x_1\ x_3\ x_2$	6	0
$x_4\ x_2\ x_1\ x_3$	5	0
$x_4\ x_2\ x_3\ x_1$	6	0
$x_4\ x_3\ x_1\ x_2$	7	0
$x_4\ x_3\ x_2\ x_1$	7	0

For the rank function (second column), these 24 orderings provide the probability distribution given below, which now can be used to evaluate the given protocol under the hypothesis of no priority effect.

Γ	Frequency	Probability
3	4	1/6
4	4	1/6
5	8	2/6
6	4	1/6
7	4	1/6
	24	1.0

In our example, the observed value of Γ (Γ_{obs}) is 3, and consequently, the hypothesis of no priority effect can be rejected at a significance level of 4/24 = .167, i.e., $P[(\Gamma_{obs} \leq 3) = .167]$.

The reader may have already recognized the similarity between this example and a very simple application of Wilcoxon's two-sample rank sum test discussed in many elementary statistics texts.[2] More explicitly, if x_i is defined as in (1) and y_i by the rank function, then the permutation distribution for Γ is equivalent to the exact sampling distribution of Wilcoxon's test statistic used for comparing two independent samples. One sample is defined by the "new" items, the second sample is defined by the "old" items, and the dependent variable is the recall rank of a particular item within the protocol. Consequently, in our illustration, two groups are formed with two ob-

[2] It should be noted that the Mann-Whitney U statistic provides a statistically equivalent version of this test. Also, in some special cases other common randomization tests may be valuable; for instance, when the "old" and "new" items can be matched on an *a priori* basis, sign tests or one-sample Wilcoxon tests might be worth considering.

servations in each, with outcomes as follows:

Group I ("New" items)	Group II ("Old" items)
1	3
2	4

Since Γ is merely the sum of the ranks in Group I and this statistic is the basis of Wilcoxon's test, the exact permutation distribution is tabled in numerous sources (for instance, see Bradley, 1968, pp. 105-117). When viewed from this perspective, a simplification of the enumerated permutation distribution becomes apparent, i.e., if we have I "new" items and n-I "old" items, then only $\binom{n}{I} = \binom{n}{n-I}$ possible rank sums need be considered. Here, $\binom{4}{2} = 6$, and the sum of 3 for the "new" items provides a probability of 1/6 = .167.

When y_i is the dichotomy function and x_i is defined as in (1), a similar equivalence can be developed between the permutation distribution for Γ and another common nonparametric test. The permutation distribution in this case is the same as the distribution of b in the following 2 x 2 contingency table with fixed marginals:

Position in protocol

	R	>R	
"New" items	b	I-b	I
"Old" items	R-b	n-R-I+b	n-I
	R	n-R	n

The distribution of b is hypergeometric and may be found explicitly by $P(\Gamma = b) = \binom{R}{b}\binom{n-R}{I-b}/\binom{n}{I}$ as in the Irwin-Fisher (or Fisher exact) test. Thus, the distribution of Γ for our simple example (i.e., the

last column in the permutation listing) could have been obtained by formula:

$$P(\Gamma = 0) = \binom{1}{0}\binom{3}{2}/\binom{4}{2} = 3/6 = 1/2;$$

$$P(\Gamma = 1) = \binom{1}{1}\binom{3}{1}/\binom{4}{2} = 3/6 = 1/2,$$

and the p-value associated with the observed value of $\Gamma_{obs} = 1$ in our simple example is 1/2. Again, more general tables for the exact permutation distribution of Γ are available merely by reinterpreting the inference problem as one of evaluating association in a 2 x 2 contingency table (e.g., see Bradley, 1968, pp. 193-203).

Although an application of Wilcoxon's and Fisher's exact tests could lead to different results for the same protocol, obviously some general consistency has to be present. In fact, David and Barton (1962, p. 190) state that the joint distribution of the Γ's based on the definitions of y_i in (2) and (3) when x_i is zero-one is approximately bivariate normal with an exact correlation of

$$-\left[\frac{3R(n-R)}{(n-1)(n+1)}\right]^{1/2}.$$

Surprisingly, this correlation depends only on the point of dichotomy R and not on the number of new items actually present. When R is close to the median object, this correlation is close to its maximum absolute value. Thus, the Γ statistics based on the two definitions of y_i are most consistent when R divides the protocol approximately in half. For instance, in our previous example with n = 4: For R = 1, the correlation between the two given statistics would be -.78; if R = 2 were chosen instead, the correlation would be -.89. For any value of R, a large-sample (i.e., $n \to \infty$) correlation can be computed merely by

substituting in the above formula.

When x_i is a general numerical variable that does not have a simple dichotomous structure that would allow the use of published tables for the corresponding permutation distribution, other procedures must be used in testing significance. Several strategies are possible, with the most obvious being to rely on a large-sample normal approximation based on the following formulas for the mean and variance of Γ (see Kendall, 1970, p. 76):

$$E(\Gamma) = (1/n)\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right);$$

$$\mathrm{Var}(\Gamma) = (1/(n-1))\left(\sum_{i=1}^{n}(x_i-\bar{x})^2\right)\left(\sum_{i=1}^{n}(y_i-\bar{y})^2\right).$$

For $y_i = i$ and x_i defined as in (1), these expressions reduce to the well-known moments for Wilcoxon's two-sample statistic:

$$E(\Gamma) = I(n+1)/2;$$

$$\mathrm{Var}(\Gamma) = (n+1)I(n-I)/12.$$

Also, when x_i is defined as in (1) and y_i as in (3), we have

$$E(\Gamma) = RI/n;$$

$$\mathrm{Var}(\Gamma) = (n-I)IR(n-R)/(n^2(n-1)).$$

In addition to the large-sample test that would compare $Z = (\Gamma-E(\Gamma))/\sqrt{\mathrm{Var}(\Gamma)}$ to the standard normal distribution, a conservative inference strategy could be obtained by applying Chebyschev's inequality and merely stating that the "true" significance level can be no larger than $1/Z^2$. (For the natural one-tailed test, Cantelli's inequality would assure us that the "true" significance level can be no larger than $1/(Z^2+1)$.) Or possibly, following Hope (1968), more

accurate significance levels could be found by generating a sample of the Γ statistics under the randomness hypothesis and using these data to approximate the exact permutation distribution. Further discussions of these latter alternatives for several related problems are given in Hubert & Levin (1976; in press, a, b).

IV

FORMAL INDICES OF PRIORITY

The previous section has suggested a randomization strategy for evaluating the relative size of Γ, and in particular, for determining whether Γ is sufficiently extreme to reject a hypothesis that the given protocol actually resulted from a random permutation of the x_i's. Obviously, since general mean and variance expressions for Γ are available, a large number of possible normalizations could be entertained. In fact, every index that has been suggested for categorical clustering could be considered here as well. For purposes of connecting the present discussion to the literature on categorical clustering, two sample indices are presented, one discussed previously by Flores and Brown (1974) called the Relative Index of Priority (RIP) and the second defined by the Z score used in the large-sample hypothesis test. We leave it to the reader to develop other more traditional candidates by generalizing the index list given in Hubert and Levin (in press a) that summarizes possible indices of categorical clustering.

For a general index Γ, the Flores and Brown RIP formula may be defined as:

$$\text{RIP} = [\Gamma - E(\Gamma)]/[\Gamma_{max} - E(\Gamma)].$$

The "Γ_{max}" term is obtained by calculating Γ for a protocol in which the given x_i's are ordered from smallest to largest. Flores and Brown

argue the merits of the RIP formula, and in so doing, repeat many of the same justifications for using an analogous index within the categorical clustering context (but see Sternberg & Tulving, 1976, for a discussion of problems associated with this index).

The second index is the Z score for Γ based on the general expectation and variance formulas:

$$Z = [\Gamma - E(\Gamma)]/\sqrt{Var(\Gamma)}.$$

Interestingly, this Z value has a very simple relationship to the product moment correlation between x_i and y_i:

$$Z = \sqrt{(n-1)}\ r_{XY}.$$

In other words, the Z score is proportional to the correlation between x_i and y_i; and furthermore, the correlation coefficient *per se* could be considered as a competitor to Z as an index of priority. Since $E(r_{XY}) = 0$, r_{XY} is "corrected" for chance in a natural way; also, r_{XY} has an especially simple permutation variance of $1/(n-1)$.

As mentioned previously, instead of merely adopting indices of priority from the categorical clustering field, other alternatives can be found in the statistical literature that have operational meaning (i.e., that have direct interpretation in terms of probability statements regarding the given protocol). For instance, using a zero-one function x_i, and y_i given by (2), Wilcoxon's two-sample test statistic results; consequently, a particularly interesting measure of priority is given by

$$\hat{\rho} = U/(I(n-I)),$$

where

$$U = [(n-I)(n+I+1)/2] - \Gamma \quad \text{(the Mann-Whitney U statistic)}.$$

Specifically, $\hat{\rho}$ can be interpreted with respect to the given protocol as follows: If a "new" and an "old" item are selected at random from the protocol, then $\hat{\rho}$ is the probability that the "new" item appears before the "old" item in the given protocol. Since U is obtained from Γ by a simple linear transformation that involves only known quantities, the permutation distribution for $\hat{\rho}$ can be found easily by using the distribution for Γ. In short, since $\hat{\rho}$ has a probabilistic interpretation with respect to the given sample data, it is unnecessary to define an unknown population parameter (or population analogue of the sample index) to justify using the statistic. Similar probabilistic arguments for several other measures of association are discussed in detail by Hays (1973, Chapters 17 and 18), e.g., for Kendall's τ and Goodman-Kruskal's λ and γ.

As a second illustration using the dichotomy definition for y_i given in (3) that leads to the 2 x 2 contingency table framework, one probabilistic measure of priority may be defined through

$$\hat{\hat{\rho}} = \frac{b(n-R-I+b)}{[b(n-R-I+b) + (R-b)(I-b)]},$$

and given the following interpretation: Suppose two items are drawn at random from the protocol with one item being "new" and the other "old," and moreover, belonging to different sections of the dichotomized protocol; then, $\hat{\hat{\rho}}$ is the probability, with respect to the given protocol, that the "new" item is in the first part of the protocol and the "old" item in the second part. Again, the permutation distribution for Γ leads directly to a permutation distribution for $\hat{\hat{\rho}}$, but in this case the form of the transformation between $\hat{\hat{\rho}}$ and b is somewhat more complex than before.

V

OTHER GENERALIZATIONS

Although most of the previous discussion has emphasized procedures that would be appropriate when x_i is dichotomous, the general index Γ was defined for and can be used when x_i characterizes a numerical variable with more than two distinct values. In addition to relying on the direct correlation index Γ, however, another approach is suggested by traditional nonparametric statistics if we assume that the, say, K distinct values of x_i actually label K classes within a traditional one-way analysis-of-variance framework. The observations within a particular category would then correspond to either the recall ranks for those items with a specific numerical label or 0-1 ranks for the portion of the protocol in which the item is located. For the former case in which recall rank is used as a dependent variable, and if x_i denotes labels that are not ordered, the appropriate nonparametric generalizations would be to either the Kruskal-Wallis one-way analysis-of-variance paradigm, or to a formulation as a contingency table with one ordered and one unordered factor (see Hubert, 1974). If x_i denotes labels that order the categories, the appropriate nonparametric generalizations would be to an ordered-category analysis-of-variance paradigm commonly used to test for a monotonic trend in a Kruskal-Wallis framework, e.g., see Hollander and Wolfe (1973, pp. 120-123) and Marascuilo and McSweeney (1967). For the 0-1 dependent

measure, the inference problem reduces to an evaluation of a K by 2 contingency table with ordered classes, and possibly, a measure such as Goodman-Kruskal's γ could be considered. In fact, since the appropriate mean and variance parameters are available for all of these generalizations (for instance, see David and Barton, 1962), the various measures used for categorical clustering could be adopted here as well.

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Educational Psychology

Joel R. Levin
Professor
Educational Psychology

L. Joseph Lins
Professor
Institutional Studies

James M. Lipham
Professor
Educational Administration

Donald N. McIsaac
Professor
Educational Administration

Gerald Nadler
Professor
Industrial Engineering

Wayne R. Otto
Professor
Curriculum and Instruction

Robert G. Petzold
Professor
Music
Curriculum and Instruction

Thomas S. Popkewitz
Assistant Professor
Curriculum and Instruction

Thomas A. Romberg
Professor
Curriculum and Instruction

Richard A. Rossmiller
Professor
Educational Administration

Dennis W. Spuck
Assistant Professor
Educational Administration

Michael J. Subkoviak
Assistant Professor
Educational Psychology

Richard L. Venezky
Professor
Computer Sciences

J. Fred Weaver
Professor
Curriculum and Instruction

Larry M. Wilder
Assistant Professor
Child Development